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METHOD AND APPARATUS FOR PROVIDING A POLYNOMIAL BASED VIRTUAL AGE ESTIMATION FOR REMAINING LIFETIME PREDICTION OF A SYSTEM

Reference is hereby made to copending:

U.S. Provisional Patent Application No. 60/255,615 filed 12/14/2000 for NEURAL NETWORK-BASED VIRTUAL AGE ESTIMIATION FOR REMAINING LIFETIME, in the names of Christian Darken and Markus Loecher, Attorney Docket No. 00P9072US;

U.S. Provisional Patent Application No. 60/255,614 filed 12/14/2000 for POLYNOMIAL BASED VIRTUAL AGE ESTIIMATION FOR REMAINING LIFETIME PREDICTION, in the names of Markus Loecher and Christian Darken, Attorney Docket No. 00P9073US; and

U.S. Provisional Patent Application No. 60/255,613 filed 12/14/2000 for MARKOV TRANSITION PROBABILITIES FOR PREDICTIVE MAINTENANCE, in the name of Markus Loecher, Attorney Docket No. 00P9074US,

of which priority is claimed and whereof the disclosures are hereby incorporated herein by reference.

Reference is also made to copending patent applications being filed on even date herewith:

METHOD AND APPARATUS FOR PROVIDING A VIRTUAL AGE ESTIMATION FOR REMAINING LIFETIME PREDICTION OF A SYSTEM USING NEURAL NETWORKS, in the names of Christian Darken and Markus Loecher, Attorney Docket No. 00P9072US01; and METHOD AND APPARATUS FOR PROVIDING PREDICTIVE MAINTENANCE OF A DEVICE BY USING MARKOV TRANSITION PROBABILITIES, in the name of Markus Loecher, Attorney Docket No. 00P9074US01, and whereof the disclosures are hereby incorporated herein by reference.

The present invention relates generally to the field of failure prediction and, more specifically to deriving an estimate of the remaining lifetime of a generic system or apparatus.

Devices and apparatus used in various fields of medicine, industry, transportation, communications, and so forth, typically have a certain useful or operational life, after which replacement, repair, or maintenance is needed. Generally, the expected length of the operational life is known only approximately and, not untypically, premature failure is a possibility. Simple running time criteria are typically inadequate to provide timely indication of an incipient failure. In some applications, unanticipated failure of devices constitutes a at least a nuisance; however, more typically, unanticipated device failure may be a major nuisance leading to costly interruption of services and production. In other cases, such unexpected failure can seriously compromise safety and may result in potentially dangerous and life-threatening situations.

In accordance with an aspect of the invention, a weighted history of monitored variables is used to compute a system's "virtual age", which is then compared with a fixed threshold.

In accordance with an aspect of the invention, a method for providing a virtual age estimation for predicting the remaining lifetime of a device of a given type, comprises the steps of monitoring a predetermined number of significant parameters of respective ones of a training set of devices of the given type, the parameters contributing respective wear increments, determining coefficients of a multivariate Hermite polynomial for modeling the wear increments determined from the training set operated to failure and whereof the respective virtual ages are normalized substantially to a desired norm value, deriving from the multivariate Hermite polynomial a formula for virtual age of a device of the given type, and applying the formula to the significant parameters from a further device of the given type for deriving wear increments for the further device.

The method will be more fully understood from the following detailed description of preferred embodiments, in conjunction with the Drawing, in which:

Figure 1 shows a diagrammatic flow chart of steps in accordance with the principles of the invention; and

Figure 2 shows a block diagram for apparatus in accordance with the principles of the invention.

In Figure 1, step 2 involves collecting data histories of devices until failure. In general this will conform to a matrix with N rows (uses) and M columns (variables).

In step 4, a polynomial of degree d is chosen and a data matrix C is computed, and solving for linear weights a using Ridge regression. Cross validation is used for optimizing as will be further explained.

In step 6, linear weights a and degree are used to compute wear increments for devices in operation.

In step 8, a warning is produced if the sum of wear increments, that is, the virtual age, crosses a user specified threshold.

10 generally indicates the use of cross validation to optimize the number of variables to be used and the degree of the polynomial.

In Figure 2, a computer 20 is equipped with data and program storage equipment 22 and a source 26 of programs for training and operating in an interactive manner as hereinafter described. Data from training sessions as further explained below is provided at 24. A device or system 28 which is being monitored provides data by way of data collection interface unit 30 to computer 20. Computer 20 provides an imminent or prospective alarm as to lifetime expiration and/or failure expectation at an alarm device 32.

The method in accordance with the present invention is widely applicable in many fields. In order to facilitate understanding of the invention and to illustrate the use of device-specific information and parameters, the invention will next be more fully described by way of an exemplary, non-limiting embodiment relating to X-ray tubes; where appropriate, generally applicable notions are also stated in the context of the specific exemplary embodiment. The example used is also appropriate in that an unexpected

failure of such an X-ray tube, for example during a critical surgical procedure, should be avoided insofar as is possible.

Suppose, $\mathbf{x}_n = (x_{1,n} \dots x_{d,n})$ is a time-series of d-dimensional measurement vectors. The individual scalars x_i could be any quantity affecting the rate of wear or ageing of the device, including directly measured physical quantities such as temperature or voltage or composite functions thereof such as, for example, power (product of voltage and current) or temperature difference, or e.g. control parameters such as load settings and time of operation. The choice of both the number d and kind of variables, which usually is only a small subset of available measurements, can be done following existing variable selection techniques. In the X-ray tube case, it turns out to have been possible to perform an exhaustive search, which selected the d unique scalars that minimized the cross validation (CV) error as will be explained in more detail below.

During the life of the device there will be typically many thousands of vectors, each of which contributes a small increment to the total wear. It is herein proposed to reduce the uncertainty in remaining lifetime estimation by the following method:

We model the wear increment by a multivariate Hermite polynomial of degree k, i.e. denote the univariate Hermite polynomial of degree k by $H_k(x)$:

$$f(\bar{x}_n) = H_0 + \sum_{j=1}^{k} \sum_{i_1+\dots+i_d=j} a_{i_1,\dots,i_d} \prod_{z=1}^{d} H_{i_z}(x_{i_z,n})$$

Note that this sum can be conveniently rewritten into a sum of M terms of the form

$$f(\bar{x}_n) = \sum_{j=0}^{M-1} a_j f_j(\bar{x}_n)$$

, where $M = \begin{pmatrix} k+d \\ k \end{pmatrix} = \frac{(k+d)!}{k!\,d!}$ is the number of coefficients a_j. The degree k and hence the number of coefficients M is a free parameter, which again should be optimized by cross validation.

Hermite polynomials can be computed in a straightforward fashion via the recurrence formula

$$H_{n+1}(x) = 2xH_n(x) - 2nH_{n-1}(x), H_0(x) = 1, H_1(x) = 2x$$

We determine the M coefficients a_j in the supervised training phase as follows:

Suppose, there are N device histories of tubes, which eventually failed, indexed by k. This constitutes our training set. Denote the number of vectors for each device by L_k. For each device we compute the M independent sums over all wear increments, which naturally depend on the M unknown coefficients:

$$C_{z,j} = \sum_{n=1}^{L_z} f_j(\vec{x}_n^{\,z})$$

This yields a (N x M) matrix $(C)_{z,j}$ and N equations for the virtual age of each device, which will have the form

$$(VirtualAge)_z = \sum_{j=0}^{M-1} a_j C_{z,j}$$

Ideally, the virtual ages for each device would be normalized to the same value, say 1 (one). In order to find the best weights, such that all virtual ages are as closes as possible to an arbitrary constant (we choose 1), we propose to minimize the sum-of-squared-error criterion function

$$J(\vec{a}) = \left\| \overline{\overline{C}} \cdot \vec{a} - \vec{1} \right\|^2 + \lambda \vec{a}^T \overline{\overline{B}} \vec{a}$$

The first term on the right side corresponds to the ordinary linear least squares regression. The additional term involving λ, is intended to improve the generalizability and avoid over fitting. This technique is referred to as ridge regression in the literature. The parameter λ should be optimized via cross validation. The matrix B is positive definite and for the X-ray tubes was taken to be the identity matrix.

In the case of missing data, i.e. if for a particular device z only a fraction f_z of data is available, we have to replace the constant vector 1 with the device dependent vector f:

$$(\overline{\overline{C}} - \lambda \overline{\overline{B}}) \cdot \vec{a} = \vec{f}$$

After determining the coefficients **a** for the N devices in the training set, it is proposed in accordance with the embodiment of the invention to estimate the remaining lifetime of devices in the same family by computing the incremental (and resulting cumulative) wear according to equation (2). Since the virtual age was normalized to one (1), the cumulative wear directly yields the fractional life that has elapsed.

The applicability of the principles of cross correlation in the context of the present invention is next addressed. K-fold cross validation is a well known technique to estimate the test error of a predictor if the available data set (size *n*) is too small to allow the split into training and test sets. Instead, we iterate the splitting process by dividing the data into a "small" part of *k* elements and use the remaining *n-k* elements for training. The test errors on the small k-set are then averaged to yield the k-fold cross validation error. In the X-ray tube example, the data set comprised approximately 70 tubes (n~70) and we chose k ~ 1-5.

It will be understood that the invention may be implemented in a number of ways, utilizing available hardware and software technologies. Implementation by way of a programmable digital computer is suitable, with or without the addition of supplemental apparatus. A dedicated system may also be used, with a dedicated programmed computer and appropriate peripheral equipment. When various functions and subfunctions are implemented in software, subsequent changes and improvements to the operation are readily implemented.

While the present invention has been described by way of illustrative embodiments, it will be understood by one of skill in the art to which it pertains that various changes and modifications may be made without departing from the spirit of the invention. Such changes and modifications are intended to be within the scope of the claims following.